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NeRF Driven 3D Crop Phenomics Intelligent Monitoring for Precision Greenhouse Agriculture

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Abstract

With the advancement of agricultural modernization, the intelligent management of greenhouses has become crucial for improving agricultural productivity. Neural Radiance Fields (NeRF), as an emerging 3D modeling and rendering technology, offers new solutions for environmental monitoring, crop growth modeling, and pest and disease early warning in greenhouses. This paper reviews the principles of NeRF, its 3D reconstruction methods, and its application progress in greenhouses. It also explores the potential of integrating NeRF with digital twin technology and analyzes the current status of plant growth models in greenhouses. The study shows that NeRF has broad prospects for application in agriculture but still faces challenges in data acquisition, model optimization, and computational efficiency. Future research needs to further integrate multi-source data and optimize neural network models to promote the intelligent management of greenhouses.

Keywords: NeRF; three-dimensional reconstruction; Agricultural greenhouse.

1. Introduction

The growing global population and demand for efficient agriculture are driving changes in agricultural production. Greenhouses, known for their efficiency and controllability, have garnered attention[1]. However, traditional management methods fall short in environmental monitoring, crop growth regulation, and pest and disease control. In recent years, with advancements in artificial intelligence and the Internet of Things, generative networks have seen rapid development, offering novel solutions for image generation, data reconstruction, and robust perception under complex conditions[2]. Among them, NeRF technology has emerged as a promising 3D modeling and rendering approach[3]. Its application in greenhouses has become a research focus, particularly in environmental monitoring, crop growth modeling[4], and early warning of pests and diseases.

2. Overview of Neural Radiance Fields Technology

2.1 Principle of Neural Radiance Fields Technology

NeRF is a 3D scene representation and rendering technique based on neural networks. Its core idea is to represent a scene as a continuous volumetric function, modeling the input viewpoints and directions through a neural network to output the radiance and density information[5] of the scene. Specifically, NeRF represents each point in the scene as a combination of volumetric density and color values, modeling these points through a neural network to achieve 3D reconstruction and rendering of the scene.

The neural network in NeRF typically adopts a Multilayer Perceptron (MLP) [6] structure, with inputs being the 3D coordinates and direction vectors in the scene, and outputs being the volumetric density and color information of the points. By integrating the density and color information of these points, images of the scene from arbitrary viewpoints can be generated. This method can effectively handle complex lighting and occlusion issues, producing high-quality 3D rendering results[3].

2.2 The Evolution of Neural Radiance Fields Technology

NeRF was introduced by Mildenhall et al. in 2020, primarily for 3D reconstruction and rendering in the fields of computer vision and virtual reality. It represents a shift in 3D modeling from traditional geometric modeling to continuous representation based on neural networks. Since its introduction, NeRF has garnered significant attention from both academia and industry. Subsequent research has focused on three main areas: First, performance optimization, which addresses the high computational cost and difficulty in real-time rendering of early NeRF implementations by optimizing neural network structures and rendering algorithms to improve computational efficiency and rendering speed. Second, data acquisition and representation, which explores methods such as sparse sampling and multi-resolution representation to adapt to different scenarios and enhance model generalization. Third, multi-view and dynamic scene applications, which introduce the temporal dimension and multi-view data to achieve 3D reconstruction and rendering of dynamic scenes[7].

2.3 The Current Application Status of Neural Radiance Fields Technology

As an emerging 3D modeling and rendering technology, NeRF has demonstrated broad application prospects across various fields. In agriculture, NeRF is utilized for 3D modeling and monitoring[8] of greenhouse environments. By creating high-precision models of temperature, humidity, and light within greenhouses, it enables farmers to better understand environmental distribution and optimize[9] crop growth conditions. Moreover, combined with image recognition technology, NeRF can monitor crop growth status and pest and disease conditions in real-time, providing support for precision agriculture. In the field of cultural heritage preservation, NeRF is employed for high-precision 3D reconstruction of historical buildings and cultural relics. This not only facilitates the digital preservation of cultural heritage but also offers immersive virtual tourism experiences to the public, enhancing awareness and protection of cultural heritage.

3. Technical Methods of Neural Radiance Fields Adapted for Agricultural Applications

3.1 Optimized Sampling Methods for Neural Radiance Fields

To e nhance the efficiency of NeRF in sampling, researchers have primarily focused on optimizing sampling strategies and improving neural network structures. Traditional NeRF employs uniform sampling in 3D space, computing the volume density and color information at each sample point, and then generating images through volume rendering. However, this method is computationally expensive, especially when dealing with complex scenes. To address this issue, several optimization methods have been proposed. For instance, hierarchical sampling first performs coarse sampling and then fine-grained sampling based on the results, effectively reducing unnecessary computations. Additionally, adaptive sampling[10] dynamically adjusts the sampling density according to the scene's complexity, avoiding over-sampling in simple areas while preserving details in complex regions. In terms of neural network structure, Fourier features have been introduced to enhance the network's ability to capture high-frequency signals, allowing high-precision 3D scene reconstruction with fewer sample points[11]. These technical optimizations not only improve NeRF's sampling efficiency but also enhance its adaptability to complex scenes, laying the foundation for real-time rendering and broader application.

3.2 Optimization of Sampling Method for Neural Radiance Fields Technology

To optimize the volume rendering techniques[12] in NeRF, researchers have proposed several algorithmic improvements. Firstly, lightweight network architectures are introduced, reducing the number of layers and neurons in the neural network while combining residual connections and batch normalization techniques to lower computational complexity without sacrificing performance. Lightweight networks streamline the architecture, reduce the number of parameters, and accelerate model training and inference. Residual connections mitigate the vanishing gradient problem in deep networks, ensuring effective information transfer, while batch normalization stabilizes the training process, enhancing model convergence speed and stability.

Secondly, sparse and multi-resolution representations are employed. These methods ignore regions with near-zero volume density and dynamically adjust the level of detail in data across different resolutions, reducing unnecessary computations. Sparse representations identify empty areas in the scene, avoiding redundant calculations and significantly improving rendering efficiency. Multi-resolution representations dynamically adjust the level of detail based on scene complexity, ensuring high-precision modeling in complex areas while reducing computational load in simpler regions.

Additionally, rendering algorithms are optimized. Techniques such as ray bundling, which processes multiple rays simultaneously, and early termination and piecewise integration methods, which reduce the number of intersection calculations and simplify the integration process, are used. Ray bundling reduces redundant calculations and improves rendering efficiency[13]. Early termination stops computations early when rays pass through transparent regions, avoiding unnecessary sampling. Piecewise integration breaks down the integration process into smaller segments, further simplifying the calculations.

These improvements not only enhance the efficiency of volume rendering but also strengthen the model's ability to handle complex scenes, providing strong support for the widespread application of NeRF technology.

4. Conclusion

This paper reviews the application of NeRF in agriculture. NeRF offers high-precision 3D modeling and real-time rendering for enhanced agricultural management. However, challenges remain in data processing, model training, real-time performance, and multimodal data fusion. Future research should focus on optimizing algorithms and improving data handling to increase NeRF's applicability in agriculture.

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